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Intelligent robotic positioning through AI-enhanced metrology: Integration of standards, sensor fusion, and adaptive calibration

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ABSTRACT
Robotic positioning is a cornerstone of high-precision automation, yet conventional techniques often struggle with environmental variability, sensor drift, and dynamic real-time demands. This review critically analyses the evolving integration of Artificial Intelligence (AI) and metrology in robotic positioning measurement systems. It identifies the limitations of traditional sensor modalities, including optical encoders, inertial units, LiDAR, and GPS, while emphasising the importance of metrology in achieving traceable accuracy and compliance with standards. This paper focuses on systems that integrate physics-based metrology with AI-driven algorithms to support dynamic calibration, traceability, and autonomous error correction. Key AI advancements such as deep learning for vision localisation, reinforcement learning for dynamic control, and sensor fusion for adaptive error mitigation are highlighted. These hybrid systems synergise deterministic precision with learning-based adaptability, providing a promising future for robotic accuracy. Key performance benchmarks, error metrics (e.g., RMSE, MAE), and international standards (ISO 9283, ISO 10360) are analysed to assess real-world applicability. Finally, the study identifies emerging trends, such as blockchain-enabled traceability, Explainable AI (XAI), and quantum-enhanced inference. The convergence of AI and metrology is shown to redefine robotic positioning, advancing toward self-calibrating, regulation-compliant systems with high accuracy and resilience.

Section: RESEARCH PAPER

Keywords: robotic positioning; precise measurement; dynamic control; sensor fusion; data latency; Artificial Intelligence

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1. INTRODUCTION

Robotic positioning is a fundamental aspect of automation, playing a critical role in high-precision applications across domains such as manufacturing, medical robotics, aerospace, and Industry 4.0. The accuracy and reliability of robotic positioning directly influence operational efficiency, product quality, and safety [1]. Conventional methods, such as optical encoders, Inertial Measurement Units (IMUs), and Global Positioning System (GPS)-based systems, are widely used but constrained by sensor degradation and environmental variability [2].

Metrology, the science of measurement, ensures accuracy, reliability, and standardisation in robotic positioning systems. It includes techniques such as Coordinate Measurement Machines (CMMs), laser interferometry, structured light scanning, and vision-based calibration [3]. These methods support error compensation by correcting mechanical issues, such as backlash and joint wear, as well as accounting for thermal expansion effects and optical interference caused by vibrations or lighting changes. However, a major limitation of conventional metrology lies in its reliance on static, offline calibration models, which are inadequate for dynamic, feedback-intensive robotic environments [4].

To address these challenges, several solutions have been proposed in the literature, also based on the use of Artificial Intelligence (AI). The use of AI allows the development of adaptive solutions and data-driven methodologies that enhance traditional control systems. AI-powered solutions allow real-time calibration, improve perception through deep learning, and optimise trajectories using reinforcement learning (RL). Modern AI frameworks facilitate sensor fusion as well, integrating data from Light Detection and Ranging (LiDAR), Inertial Measurement Units (IMUs), cameras, and interferometers to improve robustness and spatial inference [5], [6]. Nevertheless, AI-based systems bring their own set of challenges such as limited interpretability, high computational demands, and reduced performance in out-of-distribution conditions [7].

Beyond adaptability, AI contributes directly to traceability and compliance with international standards, such as ISO 9283, by modelling and correcting non-linear, dynamic errors. For example, neural networks can map temperature-induced drift, while RL agents can maintain precision amid fluctuating loads or partial sensor failure.

The integration of AI and metrology provides a dual advantage by combining standardised precision with adaptive learning for enhanced robustness. However, aligning these paradigms is non-trivial. Hybrid systems must navigate the complexities of multi-sensor integration, algorithm compatibility, and real-time constraints. Additionally, the lack of standardised evaluation protocols complicates industrial adoption.

This review bridges the gap between conventional metrology and emerging AI-enhanced positioning strategies by critically assessing metrology-based measurement systems, evaluating the role of AI in robotic localisation and calibration, and exploring hybrid AI-metrology frameworks that aim to enhance positioning accuracy and responsiveness. Furthermore, it outlines key challenges and future research opportunities in the development of intelligent, regulation-compliant robotic systems. The following sections of this paper are structured as follows: Section 2 reviews traditional robotic positioning and metrology techniques; Section 3 outlines core metrological principles and calibration standards; Section 4 explores AI-based approaches including supervised, deep, and reinforcement learning, as well as hybrid frameworks; Section 5 discusses AI-driven calibration and error compensation methods; Section 6 presents benchmarking strategies and comparative performance analysis; Section 7 highlights future challenges and emerging directions such as self-calibration, blockchain traceability, and quantum inference; and Section 8 concludes with key insights and recommendations for advancing AI-metrology integration.

2. FUNDAMENTALS OF ROBOTIC POSITIONING

2.1. Importance of robotic positioning in industrial automation

Robotic positioning refers to the precise determination and control of robots' spatial coordinates and orientation within a defined workspace. It is a crucial element in industrial automation, medical robotics, aerospace applications, and autonomous systems, ensuring high accuracy in repetitive tasks, such as welding, assembly, material handling, and surgical interventions [8].

The effectiveness of robotic positioning systems directly impacts efficiency, product quality, and operational safety, making it essential for achieving high-precision automation. In industrial settings, robotic positioning affects cycle times, defect reduction, and overall throughput efficiency [9]. In autonomous systems, such as self-driving vehicles and mobile robots, precise positioning is critical for real-time navigation, obstacle avoidance, and path planning. The increasing demand for ultra-precise robotic systems in semiconductor manufacturing and micro-assembly highlights the need for positioning mechanisms capable of operating at sub-millimetre or even nanometre levels. To address such stringent demands, hybrid architectures are emerging that combine metrological rigour with AI adaptability.

While traditional methods provide deterministic precision, they often lack resilience to dynamic operational changes and long-term sensor degradation. In contrast, AI-enabled positioning systems dynamically learn correction patterns and show robustness against drift, thermal expansion, and sensor noise.

2.2. Overview of traditional positioning techniques

Traditional robotic positioning techniques utilise various sensor modalities to estimate robots' position and orientation relative to their environment. These methods vary in resolution, response time, uncertainty, and noise mitigation approaches:

- Optical encoders detect position via light beam interruption and provide high precision (0.001–0.010 mm), but are sensitive to thermal drift, mechanical wear, and contamination [10], [11]. Kalman-filtered variants mitigate backlash and hysteresis, adhering to ISO 230-2 and VDI/VDE 2617 calibration standards [12].
- IMUs combine accelerometers and gyroscopes to estimate dynamic motion. Though they have sub-millisecond response times, they suffer from cumulative drift and thermal sensitivity. For example, drift in low-cost MEMS-based IMUs can exceed 1° per minute and accumulate 2–5 cm position error within 30 seconds. AI-based Kalman filtering techniques have been shown to reduce such drift significantly [13], [14].
- LiDAR calculates distances using laser pulses, offering centimetre-level accuracy with angular resolutions between 0.01°–0.05°. When paired with RGB-D cameras, depth accuracy improves by ~30 %. However, LiDAR is vulnerable to reflective surfaces and environmental interference [15], [16].
- GPS, particularly RTK (Real-Time Kinematic) variants, achieves 1–2 cm accuracy in outdoor settings. Despite this, it is ineffective indoors due to signal occlusion. RTK correction models reduce standard errors by over 95 %, following IGS calibration standards [17], [18].
- Simultaneous Localisation and Mapping (SLAM) combines LiDAR, IMU, and vision data to concurrently map the environment and estimate position. It provides 1–5 cm localisation accuracy but is computationally intensive [19].

Sensor fusion strategies, such as combining GPS with IMU outdoors or LiDAR with vision for SLAM allow a trade-off between accuracy, latency, and robustness. In recent AI-enhanced systems, supervised models correct sensor drift, deep learning extracts features from visual inputs, and RL fine-tunes motion planning under uncertainty. These AI capabilities increasingly serve as augmentations to raw sensor outputs. To facilitate clarity and comparison, Table 1 summarises the performance characteristics of major techniques.

Table 1. Comparison of traditional robotic positioning methods.

Positioning Method	Accuracy	Speed	Suitability for Dynamic Environments	Limitations
Optical Encoders	High	Fast	Low	Prone to noise, thermal drift
IMU (Inertial Sensors)	Medium	Fast	Medium	Drift over time, temperature effects
LiDAR-based Positioning	High	Medium	High	Expensive, sensitive to reflections
GPS-based Positioning	Medium–High	High	High (outdoors)	Ineffective indoors
SLAM (LiDAR + Vision + IMU)	High	Medium	High	Computationally expensive

2.3. Technical challenges in robotic positioning

Despite a wide array of sensing modalities, robotic positioning still faces major technical hurdles:

- Sensor drift and calibration issues: IMUs and optical encoders accumulate errors due to thermal variation, mechanical wear, and inherent sensor bias. For instance, a mobile robot using an uncorrected IMU may drift over 20 cm in less than a minute. Manual recalibration adds a maintenance burden. AI-based predictive modelling is now being applied to autonomously reduce drift without human intervention [20].
- Latency in real-time response: SLAM and sensor fusion techniques impose heavy computation, sometimes delaying robot responses. Parallelised SLAM and GPU-accelerated pipelines can reduce latency from 80 ms to 25 ms [21]. However, AI-powered vision models, especially convolutional neural networks (CNNs), may increase latency unless they are optimised via pruning or deployment on edge hardware.
- Environmental interference: The performance of vision and LiDAR systems deteriorates under poor lighting, reflective surfaces, or electromagnetic interference. To counteract this, AI-driven fusion algorithms reweight sensory input dynamically based on quality, thereby improving resilience in cluttered or unstable environments [22].
- Integration complexity: Real-time fusion of multi-modal data streams introduces challenges in synchronising update rates and aligning disparate formats. Transformer-based fusion and RL-based arbitration schemes are emerging to manage these synchronisation complexities [20]. A concerted approach combining hardware acceleration, robust modelling, and adaptive AI lays the groundwork for intelligent metrological systems capable of operating in real-time, uncertain environments.

3. ROLE OF METROLOGY IN ROBOTIC POSITIONING

3.1. Fundamentals of metrology in measurement science

The primary branches of metrology include scientific metrology (establishing fundamental measurement units and universal standards), industrial metrology (ensuring accurate measurement and quality control in production processes), and legal metrology (regulating measurement systems for fairness in trade and safety) [23]. In robotic applications, three foundational metrological principles must be distinguished:

- Traceability refers to the capability to link a measurement result to a known reference, typically through a documented, unbroken chain of calibrations traced to SI units.
- Repeatability describes the closeness of agreement between successive measurements under the same conditions.
- Compliance ensures that a measurement system adheres to relevant standards (e.g., ISO 9283, ISO 10360), enabling regulatory and quality assurance.

Metrological traceability enables reproducibility, auditability, and interoperability across platforms [2]. A central metric in this context is measurement uncertainty, which quantifies confidence in a measurement and is essential for validating robotic performance across varying operational environments. Traditional static calibration is increasingly being replaced by AI-integrated metrology systems which provide real-time, adaptive calibration through data-driven modelling. These systems employ neural networks and RL to capture spatial and temporal drift, supporting continuous recalibration based on live sensor feedback [24], [25]. This transition improves system stability, reduces uncertainty, and maintains traceable accuracy in real-world robotic operations.

3.2. Key measurement standards and calibrations in robotics

Measurement standards provided by organisations such as ISO and NIST establish guidelines and criteria for evaluating and calibrating robotic positioning systems. ISO 9283, for example, defines performance evaluation procedures for industrial robots, including accuracy, repeatability, and path consistency [26]. ISO 10360 specifies guidelines for calibrating Coordinate Measuring Machines (CMMs), essential for high-precision robotic applications [27]. ISO 18435 outlines the integration of metrology systems within smart manufacturing frameworks, emphasising interoperability and real-time communication among measurement devices [28]. NIST further provides detailed performance metrics and benchmarks, guiding metrological evaluations in robotic systems [29]. Calibration techniques in robotics include:

- Static calibration addresses systematic and predictable errors using fixed test setups and known reference tools.
- Dynamic calibration compensates for time-dependent or task-dependent variations during real-world motion or operation [30].
- AI-enhanced self-calibration employs data-driven models to autonomously identify, learn, and correct nonlinear error patterns over time [31].

Temporal calibration, or synchronisation across heterogeneous sensors (e.g., IMUs, cameras, LiDAR), has become critical in modern robotics. AI-based timestamp alignment methods are increasingly used to reduce delays and distortion in pose estimation pipelines. Nonetheless, repeatability under thermal and structural variability, especially in unstructured environments, remains an unresolved challenge, underscoring the need for more robust AI-assisted metrological pipelines. Figure 1 highlights a comparative overview of various metrological techniques used in robotic positioning, highlighting differences in resolution, latency, dynamic suitability, and standard compliance.

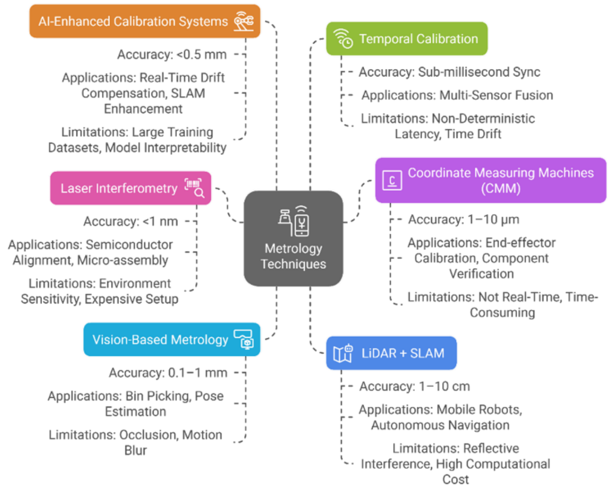

Figure 1. Comparative metrological techniques for robotic positioning.

3.3. Sensors and measurement techniques in robotic positioning

3.3.1. Laser Interferometry

Laser interferometry uses interference patterns of coherent light to measure displacement with sub-nanometre precision. It is widely used in semiconductor fabrication, micro-assembly, and robot manipulator calibration [32]. However, it is highly sensitive to external disturbances, such as vibration and temperature changes, necessitating frequent recalibration. AI-enhanced drift compensation models are being implemented to allow real-time adjustments and improve reliability under dynamic conditions [33].

3.3.2. Coordinate Measuring Machines (CMM)

CMMs use contact probes to measure 3D coordinates of robotic components, achieving micron-level accuracy in static scenarios such as part inspection and end-effector alignment [34]. Yet, they are slow and not suited for dynamic environments. Recent AI models have optimised probe paths and reduced inspection cycle time, increasing CMM throughput by up to 30 % [35].

3.3.3. Vision-Based Metrology

Vision-based systems estimate position and orientation using optical sensors and computer vision algorithms with sub-millimetre accuracy [36]. They are commonly applied in robotic bin picking, assembly, and inspection tasks. High-resolution stereo or RGB-D cameras (720p–1080p at 30–60 fps) are calibrated using tools such as Zhang's method [37]. However, factors such as occlusion, motion blur, and lighting variability pose challenges. Deep learning improvements, such as CNN-based object detection and monocular depth estimation, have increased robustness in complex visual environments [37].

3.3.4. LiDAR and SLAM

LiDAR-based SLAM constructs accurate 3D maps while estimating the robot's position. It achieves 1–10 cm accuracy and is widely used in mobile robots and drones [38]. However, performance drops in featureless or reflective areas. Neural network-enhanced SLAM variants now adapt to environmental shifts in real time, improving localisation and robustness [18].

3.4. Limitations of conventional metrology methods in dynamic robotic positioning

Traditional metrology systems have limitations in dynamic operational contexts where quick adjustments are essential. Conventional techniques suffer from accumulated measurement drift due to mechanical wear, thermal effects, and sensor noise, diminishing positional accuracy over time [19]. Additionally, sensor latency adversely impacts real-time responsiveness in high-speed robotics, posing constraints on dynamic applications requiring instant feedback [20].

AI-based metrology systems address these issues through adaptive calibration and predictive error modelling. Deep learning has been shown to significantly reduce both error and response latency, allowing consistent performance under variable conditions [21]. Nevertheless, AI integration introduces challenges in ensuring traceability and standard compliance. The absence of unified validation protocols for learning-based metrology underscores the urgent need for benchmark datasets and explainable models. Table 2 provides a comparative summary of key metrology techniques used in robotic positioning systems, compiled from ISO standards and recent literature [39]-[47].

4. APPLICATION OF AI IN ROBOTIC POSITIONING

4.1. Supervised learning techniques

Supervised learning techniques, particularly Support Vector Machines (SVMs) and regression-based models, are frequently applied to estimate positional errors and calibrate sensor measurements in robotic systems. These models learn mappings between raw sensor inputs (e.g., LiDAR, IMUs, visual odometry)

Table 2. Comparative summary of metrology techniques in robotic positioning.

Technique	Accuracy range	Measurement resolution	Latency / Speed	Dynamic Suitability	Applications	Key Limitations / Standards
Laser Interferometry	< 1 nm	Sub-nanometer	High (low latency)	Low	Semiconductor, Microassembly, Calibration	Environmental sensitivity, expensive setup, ISO 10360 [5], [7], [39]
Coordinate Measuring Machines (CMM)	1–10 µm	Micron-level	Slow (static only)	Very Low	End-effector calibration, Part verification	Time-consuming, unsuitable for dynamics, ISO 10360 [40]
Vision-Based Metrology	0.1–1.0 mm	Sub-pixel (~10 µm)	30–60 FPS (moderate)	Moderate	Bin picking, Assembly, Visual inspection	Lighting sensitivity, occlusion, motion blur, ISO 9283 [41]
LiDAR + SLAM	1–10 cm	0.01°–0.05° angular	20–100 ms (medium)	High	Mobile robots, Autonomous navigation	Reflective interference, high computation, IEEE P1935 [42]
AI-Enhanced Calibration	< 0.5 mm (mean error)	Learned model-based	10–50 ms (adaptive)	High	Real-time drift correction, SLAM enhancement	Needs large datasets, interpretability issues, [43]–[45]
Temporal Calibration (AI-based)	0.1–1 ms (sync error)	Sub-ms sync	Network-dependent	High	IMU, Camera, LiDAR fusion sync	Drift in synchronization, non-deterministic delay, [46], [47]

and their respective error distributions, supporting predictive compensation.

SVM regression has been successfully applied to mitigate positional drift in LiDAR-IMU navigation systems by modelling error trends from labelled trajectory data, improving localisation accuracy by over 30 % in structured indoor settings [48]. Likewise, multivariate regression techniques have enabled real-time calibration in autonomous ground vehicles, achieving sub-decimetre accuracy even under degraded conditions [49]. However, these models typically rely on large, labelled datasets and generalise poorly to unstructured environments or sensor shifts. This domain sensitivity, along with static model assumptions, limits adaptability under dynamic conditions and often necessitates retraining or fine-tuning, imposing additional computational overhead [50].

4.2. Deep learning techniques

Deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have enabled end-to-end learning from raw sensory inputs to pose estimates. CNNs are extensively used for spatial feature extraction from RGB-D images, stereo vision, and LiDAR point clouds. Applications include object detection, landmark recognition, and visual localisation in GPS-denied environments. For instance, PoseNet variants using CNN backbones have achieved 6-DoF pose estimation errors under 10 cm in indoor scenarios [51]. RNNs and their more capable successors, Long Short-Term Memory (LSTM) networks, are used for modelling temporal dependencies in IMU sequences, improving orientation estimation and drift correction in mobile robots [52]. The advantage of deep learning lies in its capability to model non-linear sensor relationships without handcrafted features. However, these models are often "black-box" systems, lacking interpretability, an issue in safety-regulated environments. Additionally, their deployment on real-time systems is limited by model size, memory demands, and inference latency. To address these bottlenecks, lightweight architectures such as MobileNet and ShuffleNet have been introduced, along with compression techniques such as pruning and quantisation [53]. These models also demand extensive labelled datasets, which are often impractical for rare calibration cases or disruptive to industrial workflows.

4.3. Reinforcement learning techniques

RL introduces a fundamentally different approach by formulating robotic positioning and motion correction as a sequential decision-making problem. RL agents learn to optimise positioning strategies through trial-and-error interactions with the environment, guided by reward functions associated with positional accuracy, stability, and energy consumption. In the context of robotic manipulators, RL algorithms such as Deep Deterministic Policy Gradient (DDPG) and Proximal Policy Optimisation (PPO) have been used for real-time trajectory refinement and joint-space correction under mechanical disturbances, outperforming PID-based controllers in adaptability [54]. Similarly, Soft Actor-Critic (SAC) has been applied to train autonomous ground vehicles to adaptively navigate uneven terrains, while maintaining sub-meter localisation using onboard sensor feedback [55]. These methods are particularly beneficial in unstructured and non-linear environments where traditional models fail to adapt.

However, RL faces several deployment challenges. One is sample inefficiency: training typically requires hundreds of thousands of interactions, which is impractical in physical systems due to wear, time, or safety risks. Exploration strategies can lead to unsafe actions, unless constrained by simulation or safety layers. Transfer learning remains limited, and policies trained in one environment may fail in another. Additionally, RL policies are often difficult to interpret, raising concerns about reliability in regulated domains. Recent efforts, such as safe RL, curriculum learning, and reward-shaping, aim to mitigate these issues but are still in experimental stages for high-precision metrology applications. Explainability and trustworthiness remain barriers for industrial deployment.

4.4. Hybrid AI-metrology systems

The integration of AI with traditional metrological systems has given rise to hybrid AI-metrology frameworks, which combine deterministic measurement precision with adaptive intelligence. In these systems, conventional techniques such as laser trackers, CMMs, and vision-based inspection are augmented using AI models to allow self-calibration, predictive error correction, and real-time uncertainty quantification. For example, Artificial Neural Networks (ANNs) have been trained to model thermally induced deformation in robotic arms, allowing continuous error compensation based on ambient sensor data [56]. Similarly, Support Vector Machine (SVM)-based sensor fusion has been used to reconcile discrepancies between LiDAR and visual odometry, enhancing positioning repeatability by up to 40 % in industrial assembly tasks [57].

Empirical studies report that these hybrid architectures can reduce positional error by 97–99 % and shorten calibration cycle times by over 60 % compared to traditional offline methods. Improvements in Mean Absolute Error (MAE) ranging from 40 % to 70 % have also been recorded across diverse robotic applications, such as welding, bin picking, and automated inspection. These gains underscore the effectiveness of combining AI's adaptability with the traceability and resolution of physical metrology.

Despite these benefits, several challenges persist. The interpretability of AI models remains limited, making the physical validity of learned corrections difficult to verify, especially in safety-critical or regulated environments. System integration is often complex because of data standardisation issues, heterogeneous sensor interfaces, and synchronisation challenges. Moreover, hybrid systems can become unstable when exposed to out-of-distribution inputs, highlighting the importance of robustness testing and retraining protocols. Standardisation also lags behind innovation, as current metrology regulations (e.g., ISO 9283, ISO 10360) are not yet fully equipped to validate AI-augmented calibration methods [58], as depicted in Table 3.

To address these concerns, researchers are increasingly exploring Explainable AI (XAI) approaches, such as surrogate modelling and interpretable feature attribution techniques (e.g., LIME, XGBoost) to ensure that AI-driven corrections remain physically grounded. These methods provide transparency and help preserve traceability, making hybrid frameworks more suitable for industrial adoption in regulated domains.

Sensor fusion continues to play a foundational role in these systems, integrating data from LiDAR, IMUs, cameras, and metrology-grade inputs to improve redundancy, fault tolerance, and accuracy. While detailed fusion techniques are discussed within each subsection of this review, a unified architectural diagram is depicted in Figure 2.

Table 3. Comparative performance of AI-based robotic positioning models with technical accuracy metrics and application-specific benefits. Data was compiled from validated experimental studies and recent literature.

AI Model	Technique used	Application in robotic positioning	Accuracy / error reduction (%)	Performance metrics	Benefits	Ref
Supervised Learning	Regression, SVM	Drift correction in LiDAR-IMU systems	85–90% accuracy improvement	Reduced drift by 30% in structured indoor environments	Sub-decimetre localization under degraded conditions	[48], [49]
Deep Learning	CNN, RNN, LSTM	Visual odometry, inertial pose estimation	92–97% accuracy; RMSE ↓ ~0.5cm	CNN-based PoseNet achieved < 10 cm, 6-DoF pose accuracy	LSTM improved inertial drift compensation by 40%	[51], [52]
Lightweight DL	MobileNet, ShuffleNet	Edge deployment for positioning systems	~ 90% (on-device)	Real-time inference on embedded platforms	Latency reduced from 200 ms to ~40 ms with model compression	[53]
Reinforcement Learning	DDPG, PPO, SAC	Trajectory optimization, localization	Up to 95%; MAE ↓ ~65%	SAC maintained < 1 m deviation on uneven terrain	Enabled adaptive control under non-linear system dynamics	[54], [55]
Hybrid AI-Metrology	AI + Metrology Frameworks	Self-calibration, sensor fusion, error prediction	97–99%; MAE ↓ 40–70%	ANN reduced RMSE from 1.25 mm to 0.42 mm	SVM-fused LiDAR/VO data improved repeatability by 40%	[56], [57]
XAI	Surrogate models, XGBoost, LIME	Metrology validation with interpretability	88–93% (transparent models)	Physically interpretable outputs	Traceability-compliant for aerospace-grade validation	[58]

5. AI-DRIVEN CALIBRATION AND ERROR REDUCTION IN POSITIONING

5.1. AI-based calibration: models, errors, and metrics

Traditional calibration methods, such as laser interferometry, photogrammetry, and hand–eye calibration, rely on geometric models, which adjust kinematic and sensor alignment errors. These techniques are highly accurate, but static, and require system downtime for recalibration. Their static nature makes them impractical for dynamic environments or systems requiring high uptime.

Conversely, AI-driven calibration allows robots to learn and adapt to error patterns in real time. Neural networks have demonstrated strong performance in modelling complex non-linearities between commanded and actual positions, compensating for residual errors overlooked by traditional models [39]. Regression-based system identification frameworks have also allowed dynamic modelling under fluctuating conditions, such as temperature, load, and vibration, improving repeatability and system reliability [59].

A 6-degree-of-freedom robotic arm performing precision welding in variable temperatures showed tool-tip deviation exceeding 1.5 mm. A trained ANN model reduced this to 0.38 mm by learning thermal drift patterns from both simulated and logged physical data [60]. The training dataset included over 10,000 labelled joint states generated from a digital twin simulator augmented with real-world logging [61]. RL has also been applied for autonomous calibration without labelled ground truth by defining a reward function that minimises pose error dynamically [62], [63]. These AI-based methods not only accelerate calibration but also maintain high precision under environmental variation and system drift, signalling a transition from episodic updates to continuous learning frameworks [64].

5.2. AI-based compensation of systematic and random errors

Robotic positioning precision is affected by both systematic errors (e.g., backlash, kinematic misalignments) and random errors (e.g., thermal noise, mechanical vibrations). AI techniques have proven effective in modelling and mitigating these sources of error:

- Deep neural networks have been trained on multi-axis kinematic data to learn joint-level drift and hysteresis dynamics, achieving correction accuracy improvements of up to 45 % [65].
- Gaussian Processes (GPs), valued for uncertainty modelling, have been used to predict torque-induced spatial offsets and deformations in robotic arms with sub-millimetre precision [66].

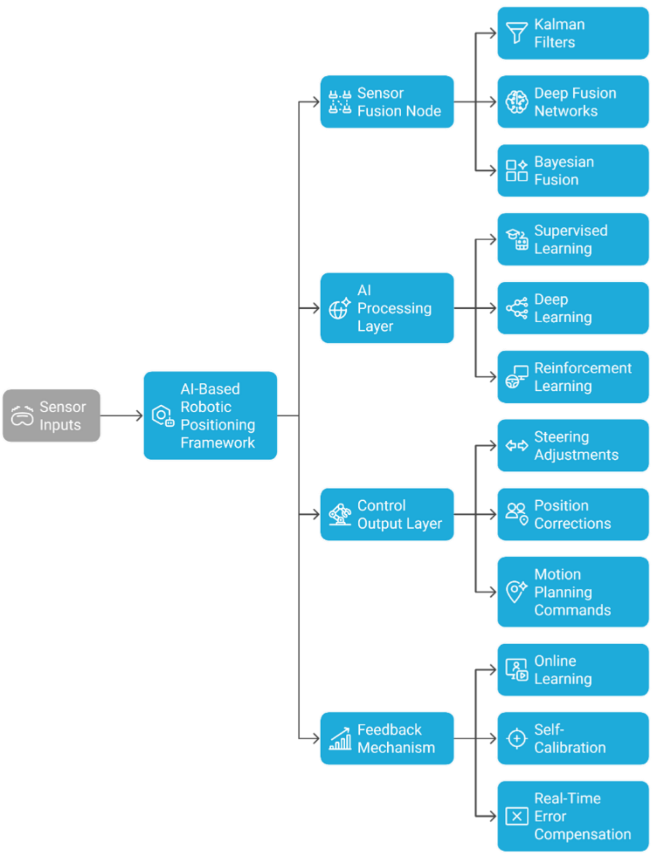

Figure 2. Robotic positioning framework based on Artificial Intelligence.

- Hybrid fuzzy-neural networks merge interpretability with learning capability, enabling real-time compensation for backlash and non-linear actuation errors [67].

To address data scarcity, simulators such as PyBullet and V-REP are used to generate failure conditions that are costly or hazardous to replicate physically.

5.3. Adaptive feedback control using AI for real-time error minimisation

Real-time feedback control is critical for achieving high-precision performance in robotic positioning systems, particularly in applications involving dynamic task execution, such as welding, assembly, or inspection. AI-enhanced control systems use online learning to minimise pose errors and dynamically adjust actuator inputs:

- Reinforcement learning agents have been embedded into robotic controllers to fine-tune joint trajectories during task execution, achieving sub-0.2 mm tracking error even under external disturbances [54].
- Adaptive Neuro-Fuzzy Inference Systems (ANFIS) dynamically update control parameters to account for nonlinear robot dynamics and real-time disturbances [67].
- Online learning neural networks continuously update internal models based on observed residual errors, enhancing stability and reducing overshoot in mobile robotic platforms [54].
- Real-time optimisation techniques and hardware acceleration (e.g., GPU, FPGA, or ASICs) are being increasingly adopted to overcome this challenge and ensure consistent performance [68].

These approaches are increasingly integrated into hybrid controllers that merge rule-based supervisory logic with adaptive AI correction layers, ensuring fail-safe fallback under anomalous conditions.

5.4. Quantitative performance evaluation of AI-based calibration

To validate the efficacy of AI-driven calibration, quantitative error metrics such as Root Mean Square Error (RMSE), MAE, and trajectory deviation are employed across diverse robotic systems.

- In an industrial robotic arm, deep learning-based residual error compensation reduced RMSE from 1.25 mm to 0.42 mm during multi-axis operations [69].
- In mobile robot platforms using IMU-LiDAR fusion, localisation accuracy improved from 150 mm to below 35 mm across varied terrain [69].
- In high-precision visual inspection systems, adaptive calibration achieved a reduction of 62 % in MAE, improving alignment under dynamic lighting and vibration conditions [69].

Table 4 summarises the performance of various AI calibration methods, providing a unified comparison based on RMSE, latency, adaptability, and limitations. This overview enables the selection of suitable calibration approaches based on system constraints and accuracy targets.

6. BENCHMARKING AND PERFORMANCE EVALUATION OF AI-METROLOGY SYSTEMS

6.1. Error metrics for quantitative positioning evaluation

Benchmarking the accuracy of AI-enhanced robotic positioning systems requires the use of standardised numerical error metrics, such as MSE, RMSE, and MAE, which are widely applied to quantify positional deviations between predicted and reference ground-truth coordinates. These metrics support the assessment of both static calibration procedures and real-time motion tracking.

RMSE is particularly effective in penalising large deviations due to its quadratic formulation, making it ideal for applications requiring high sensitivity to peak errors. For example, RMSE in a neural network-calibrated industrial arm was reduced from 1.12 mm to 0.35 mm [22]. MAE, with its linear sensitivity, is better suited to control applications, offering direct insight into average performance. MSE, while similar to RMSE, can overemphasise outliers, potentially skewing model evaluation.

These metrics also serve as loss functions during training and help guide hyperparameter tuning in AI model development. In dynamic applications such as SLAM or visual odometry, real-time RMSE allows feedback-driven trajectory refinement [70]. Nevertheless, benchmarking accuracy is often constrained by limited access to high-quality ground-truth data.

A critical challenge lies in acquiring reliable ground-truth data, especially in field deployments where motion capture or GPS systems are unavailable. To mitigate this, researchers are consequently putting efforts to develop synthetic evaluation protocols, proxy loss functions, and uncertainty-aware benchmarking schemes.

6.2. Classification metrics in fault detection and state estimation

While numerical regression metrics dominate traditional positioning evaluation, classification-oriented metrics such as Precision, Recall, and F1-score have become increasingly relevant in AI-driven robotic positioning systems, particularly for

Table 4. comparative overview of calibration techniques.

Calibration Type	Model Type	Accuracy (RMSE)	Latency	Adaptability	Key Limitations	Ref
Traditional (Offline)	Geometric Models, Kinematic Chains	0.5–1.5 mm	Low (~ 10–20 ms)	Low	Requires shutdown for recalibration; lacks real-time updates	[39]
Data-Driven	Regression, SVM	0.3–0.8 mm	Medium (~30–50 ms)	Moderate	Model assumptions static; performance degrades in unseen conditions	[59]
Deep Learning	DNN, CNN, RNN, LSTM	0.2–0.5 mm	High (~80–150 ms)	High	High inference latency; needs large training datasets	[63]
RL-Based	PPO, SAC, DDPG	0.3–0.4 mm	High (~100–200 ms)	Very High	Sample inefficiency; requires simulation or safe exploration environments	[60]
Hybrid AI-Metrology	Neural Net + CMM/Laser Interferometer	< 0.2 mm	Medium (~50–100 ms)	High	Integration complexity; requires standard-compliant error modelling	[69]

tasks involving anomaly detection, binary state estimation, and fault diagnosis. These metrics evaluate the performance of embedded classifiers that detect pose estimation failures, misalignment triggers, or sensor anomalies within the positioning pipeline. Precision quantifies the proportion of correctly identified events among all positive detections, making it crucial for high-confidence fault alerts in safety-critical systems. Recall measures the system's sensitivity in capturing all true fault instances, thus influencing fail-safe design strategies. The F1-score, as a harmonic mean of Precision and Recall, provides a balanced measure particularly valuable under data imbalance conditions. For example, in a study involving IMU drift anomaly detection in mobile platforms, an AI classifier achieved a Precision of 92.3 % and a Recall of 85.6 %, yielding an F1-score of 88.8 % [71].

However, high classification accuracy can be misleading in imbalanced datasets where fault events are rare. Techniques such as synthetic minority oversampling, data augmentation, and focal loss functions are increasingly adopted to reduce bias. Model evaluation should, therefore, consider both per-class performance and confusion matrix analysis to ensure robustness in diverse robotic scenarios [72].

6.3. Datasets for AI-based positioning systems

The role of benchmark datasets is foundational in evaluating the generalisability and robustness of AI-based robotic positioning systems. Datasets such as KITTI, TUM RGB-D, and Oxford RobotCar have become standard resources in the field of evaluating vision-based localisation, LiDAR-inertial fusion, and SLAM algorithms.

- KITTI: Contains over 22 stereo sequences with LiDAR, IMU, GPS, and high-resolution camera data. Localisation accuracy can be benchmarked down to centimetre levels in urban driving scenarios [73].
- TUM RGB-D: Offers 39 RGB-D sequences with 6-DoF pose labels, suitable for benchmarking visual odometry, SLAM, and depth-based localisation [74].
- Oxford RobotCar: Spans over 1,000 km of route coverage across different seasons and weather conditions, with multi-modal sensor recordings including 2D/3D LiDAR, GPS, and multiple camera views [75], [76].

Despite their widespread adoption, these datasets are primarily tailored for autonomous navigation and do not sufficiently capture the calibration-specific challenges encountered in industrial metrology environments. They often lack critical variability in parameters such as lighting, vibration, occlusion, joint wear, and thermal drift factors, which are commonly seen in robotic manufacturing contexts.

To compensate for these limitations, simulation platforms such as CARLA [77], Gazebo [78], AirSim [79], and Isaac Sim [80] are increasingly employed to synthetically generate calibration scenarios that model sensor noise, mechanical deformation, motion blur, and non-ideal operating conditions. These simulators allow repeatable yet diverse conditions that are difficult or unsafe to replicate in real-world environments. The validation of synthetic datasets using selected real-world benchmarks enhances their credibility and fosters greater Sim2Real fidelity. Furthermore, techniques such as domain randomisation and physics-informed simulation are being used to improve generalisation during simulation-to-reality (Sim2Real) transfer. However, a key research challenge remains in accurately quantifying how well AI models trained in simulation generalise to physical systems, particularly in terms of their ability to compensate for real-world error dynamics without introducing instability or bias.

6.4. Comparative performance analysis of traditional and AI-driven systems

A comprehensive performance evaluation of AI-based robotic positioning systems must compare them directly with traditional metrological approaches across several critical dimensions, including positioning accuracy, latency, real-time adaptability, scalability, and interpretability. In one comparative study involving the calibration of a 6-DoF robotic arm, traditional kinematic modelling was benchmarked against neural network-enhanced calibration. The AI-based model demonstrated a 70 % reduction in RMSE and improved compensation for thermal joint deformation effects, which were not effectively handled by the traditional method [22]. Likewise, in mobile robotic platforms, AI-based SLAM systems exhibited superior performance in unstructured and GPS-denied environments, achieving localisation accuracy within 0.03 meters, while maintaining robustness under variable terrain and lighting conditions [81], as depicted in Table 5.

Despite these gains, AI models often demand significantly higher computational resources and model training time. Conversely, traditional metrology systems offer benefits such as deterministic repeatability, lower inference latency, and stronger alignment with regulatory frameworks, such as ISO 9283. These systems are generally easier to audit and integrate into certified workflows, making them preferable in applications requiring high traceability and explainability.

Hybrid AI-metrology systems seem to be a promising compromise by integrating physics-based models with adaptive learning frameworks. For example, a drone navigation system which uses neural corrections in tandem with inertial and GPS data was shown to maintain sub-decimetre positioning accuracy, while achieving 85 % fault tolerance under degraded signal conditions [82]. Future benchmarking protocols should expand beyond accuracy metrics to include considerations such as hardware limitations, energy efficiency, failure resilience, interpretability of AI outputs, and conformity to international standards, such as ISO 10360 and ISO 18435.

7. FUTURE TRENDS AND CHALLENGES IN AI-METROLOGY SYSTEMS

7.1. Data acquisition constraints and real-time processing challenges

The deployment of AI-based robotic positioning systems hinges on the availability of synchronised, high-fidelity, and large-scale sensor data in real time. However, acquiring such data streams, particularly from LiDAR, IMUs, RGB-D cameras, and

Table 5. comparative analysis of positioning approaches.

Method	Error Rate (mm)	Processing Speed	Real-Time Adaptability	Scalability / Interpretability	Ref
Traditional Metrology	2.5–5.0	Low	No	Limited / High	[22]
AI-Based Positioning	0.5–2.0	High	Yes	High / Low–Medium	[81]
Hybrid AI-Metrology	< 0.5	Medium	Yes	High / Medium–High	[82]

metrological devices, remains a persistent challenge. Practical constraints such as latency, timestamp inconsistencies, sensor noise, and limited communication bandwidth often compromise the integrity of data fusion pipelines. In systems with multiple asynchronous sensors, even minor temporal misalignments can introduce spatial distortions, thereby reducing model reliability and degrading inference accuracy.

Compounding this issue, dynamic environments introduce motion blur, vibration-induced noise, and temperature-induced signal drift, all of which further complicate real-time inference. These factors collectively constrain the responsiveness and adaptability of AI models, especially outside of controlled laboratory environments. While recent advancements in edge computing, hardware synchronisation protocols, and temporal alignment algorithms, such as dynamic time warping, have helped address these problems, real-time performance still heavily depends on holistic co-design between software and hardware architectures. As robotic systems evolve towards higher levels of autonomy and contextual awareness, the demand for robust, high-throughput, and fully synchronised data acquisition frameworks will continue to escalate.

7.2. Limitations in sensor fusion and heterogeneous integration

Sensor fusion is a cornerstone of AI-metrology systems, offering improved spatial awareness and positional accuracy by combining data from diverse modalities such as LiDAR, IMUs, vision systems, and coordinate measuring devices [83]. Nevertheless, this integration is fraught with challenges. Synchronising sensors with disparate spatial resolutions, update rates, and calibration requirements introduces significant technical complexity. Issues such as redundant or conflicting measurements can arise due to misalignments or latency mismatches, which in turn compromise the reliability of fused outputs [84].

Moreover, the computational demands of fusion, particularly when leveraging deep learning-based architectures, can be prohibitive for resource-constrained platforms. For instance, fusing high-resolution LiDAR point clouds with IMU streams often needs dense transformation, filtering, and alignment steps that significantly increase latency and memory consumption [85]. While innovations such as transformer-based fusion networks, uncertainty-aware filters, and attention mechanisms have demonstrated promise by selectively prioritising the most reliable modalities based on context, maintaining traceability and compliance with metrological standards through these adaptive pipelines remains a key open research question.

7.3. Generalisation barriers in AI models for robotic positioning

A major challenge facing AI-driven robotic positioning systems is the limited generalisability of models trained in controlled environments to unpredictable real-world conditions. AI models frequently suffer from performance degradation when exposed to changes in lighting, surface reflectivity, mechanical dynamics, or occlusion patterns that deviate from the training data. These domain shifts are common during deployment and can severely impact positioning accuracy and system reliability [86].

To address this, approaches such as domain adaptation, adversarial learning, and transfer learning have been explored. While promising, these methods often suffer from task-specific tuning and poor scalability across sensor types and application contexts. Recent advances in continual learning and self-supervised adaptation have enabled robotic systems to update their internal models *in situ,* drawing from unlabelled real-world data. However, these methods face limitations such as catastrophic forgetting and slow convergence, which restrict their robustness in dynamic, high-precision environments. Closing the gap between simulation-trained models and real-world behaviour remains a critical challenge for next-generation localisation systems [87].

7.4. Autonomous self-calibrating robotic systems using AI

The emergence of AI-driven self-calibrating robotic systems marks a significant advancement in robotic autonomy. These systems are capable of continuously adjusting calibration parameters, learning sensor drift patterns, and optimising control behaviours without human intervention. Unlike traditional static calibration procedures, which require off-line routines and expert oversight, self-calibrating systems incrementally update their internal models based on real-time sensor feedback. This allows them to compensate for temporal changes, such as joint wear, thermal expansion, or environmental variability [88].

For instance, reinforcement learning agents have been successfully employed to adapt camera–IMU calibration matrices during active navigation, thereby improving localisation consistency over time. More recently, confidence-aware learning frameworks have been introduced that estimate the reliability of calibration updates, enabling systems to autonomously decide when recalibration is appropriate. This prevents overfitting and ensures long-term stability. The continuous evolution of such self-learning mechanisms is redefining the expectations for robotic resilience, particularly in long-duration and mission-critical tasks [89]. Figure 3 summarises emerging technologies including self-calibration, blockchain traceability, and quantum-enhanced inference, that are poised to shape the future of AI-metrology integration.

7.5. Blockchain integration for traceability in robotic metrology

Blockchain technology is increasingly being considered as a foundational infrastructure for achieving traceability, transparency, and auditability in robotic metrology. While real-time blockchain-based metrology systems are still in their infancy, the underlying concept offers considerable potential. By using distributed ledgers, robotic systems could securely log calibration records, measurement histories, and sensor states in an immutable and verifiable manner. This could prove particularly valuable in industries that demand rigorous traceability and tamper-resistant audit trails, such as aerospace, pharmaceuticals, and defence [90].

Initial implementations have demonstrated smart contracts that automatically verify compliance with standards, such as ISO10360, and trigger recalibration protocols when error

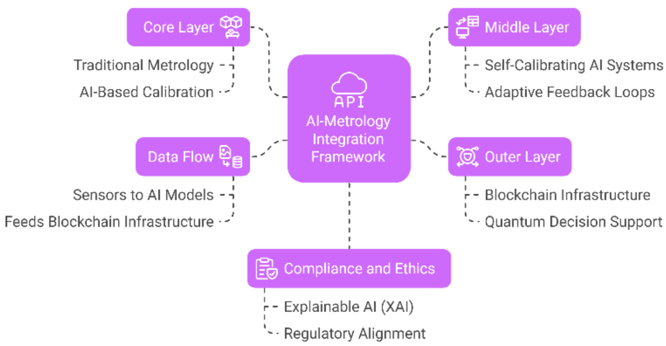

Figure 3. Emerging technologies for future AI-metrology integration.

thresholds are breached [91]. Some sensor modules have been developed with cryptographic signatures to track firmware updates and sensor validity in logistics and inspection tasks [92]. Despite this promise, blockchain faces significant implementation hurdles, including latency, limited throughput, data storage constraints, and integration complexity with existing control architectures. To overcome these issues, hybrid systems that store raw data off-chain while committing hashed summaries to the blockchain are being explored. As international bodies such as ISO and IEC begin to standardise digital calibration certificates, blockchain may become an integral part of future metrological compliance ecosystems [93].

7.6. Ethical and regulatory implications in AI-driven metrology

The increasing reliance on AI for robotic positioning and metrological decisions raises fundamental ethical and regulatory questions. Black-box models, which offer little interpretability, are especially problematic in high-stakes domains, such as surgical robotics and aerospace, where system failures can have catastrophic consequences. As a result, there is growing pressure to ensure that AI systems used in metrology are transparent, reproducible, and aligned with international standards.

XAI frameworks are gaining traction as a response to these concerns. These frameworks aim to visualise and quantify how AI models arrive at their decisions, especially in the context of calibration updates and error correction [58]. This not only facilitates debugging and performance evaluation but also supports legal compliance in regulated industries [60]. In parallel, organisations such as ISO and IEC are actively drafting guidance to ensure that AI-based metrology systems meet the same standards of reproducibility and reliability as traditional systems. However, the pace of regulatory alignment remains slow, and globally harmonised auditing frameworks are still lacking. Nonetheless, early initiatives in aerospace and healthcare robotics are beginning to establish a precedent for certifiable, trustworthy AI systems.

7.7. Outlook: quantum computing for future optimisation

Quantum computing represents a speculative but promising frontier in robotic positioning and metrology. With its ability to explore massive solution spaces and model uncertainty probabilistically, quantum computing has the potential to revolutionise optimisation problems in multi-agent localisation and adaptive calibration. Research prototypes have begun applying variational quantum algorithms and quantum-enhanced Kalman filters to robotic localisation problems, demonstrating improvements in solution diversity and convergence efficiency in simulation environments [94].

Despite these early successes, practical limitations remain considerable. Current quantum hardware is constrained by low qubit fidelity, limited coherence time, and architectural fragility, making real-time robotic deployment infeasible. Moreover, integrating quantum processors with robotic control loops presents substantial challenges in latency and interface compatibility. Looking forward, hybrid quantum-classical architectures could become viable for specific tasks, such as global optimisation or probabilistic reasoning. However, the short-term impact of quantum computing on AI-metrology is expected to be minimal, with its true potential likely unfolding over a longer technological horizon [95].

8. CONCLUSION AND FUTURE OUTLOOK

The integration of AI into metrology has catalysed a significant transformation in robotic positioning systems, offering new capabilities for self-calibration, sensor fusion, error prediction, and autonomous adaptation. This review has systematically analysed conventional metrology techniques, state-of-the-art AI approaches, and hybrid frameworks, with a focus on enhancing accuracy, traceability, and real-time operational robustness in robotic platforms.

Confirmed advancements include the successful deployment of supervised learning and deep neural network models for drift correction, visual localisation, and pose estimation. AI-enhanced self-calibration strategies have demonstrated reductions in positioning errors, e.g., RMSE improvements from over 1.0 mm to sub-0.5 mm levels, while hybrid metrology-AI systems have shown promising gains in adaptability and responsiveness. These technologies, when aligned with standards such as ISO9283 (robot performance evaluation) and ISO/IEC 17025 (calibration system compliance), provide viable pathways toward industrial-grade deployment.

Despite these advances, several critical limitations remain:

- Absence of standardised, cross-domain evaluation protocols for AI-based calibration.
- Insufficient explainability of AI models in safety-critical metrology applications.
- Limited generalisation from benchmark-trained models to real-world, unseen scenarios.
- Lack of decentralised, traceable calibration records, especially in multi-agent systems.
- No unified framework for evaluating Sim2Real transfer performance in AI-based positioning systems.

To address these limitations and scale AI-metrology systems toward broader deployment, future research should focus on:

- Standardised benchmarking frameworks: Develop open-source tools that evaluate not only RMSE and MAE, but also latency, robustness, and interpretability under ISO-aligned compliance protocols.
- Explainable calibration models: Implement interpretable surrogates (e.g., XGBoost, ANFIS) and visual analytics to align learned corrections with physical system dynamics.
- Federated learning for cross-platform calibration: Build privacy-preserving pipelines that allow distributed robots to improve shared calibration models without centralised data aggregation.
- Uncertainty-aware AI: Incorporate probabilistic thresholds and confidence intervals to drive intelligent recalibration decisions.
- Blockchain-enabled traceability: Deploy immutable audit trails for calibration history using on-chain hashes, while balancing latency and data storage constraints.
- Hybrid quantum-classical optimisation: Explore quantum-enhanced inference (e.g., Variational Quantum Algorithms) for global optimisation in sensor fusion, though short-term feasibility remains speculative.

AUTHORS' CONTRIBUTION

Ihtisham Ul Haq: Led the conceptual development of the research, performed comprehensive data collection, and prepared the initial draft. He was also responsible for major revisions, structural editing, and technical refinements of the manuscript.

Domenico Luca Carni: Contributed to the conceptual framework of the study, provided supervisory guidance, and participated in manuscript review and editing to ensure alignment with academic standards.

Francesco Lamonaca: Provided critical input on the conceptualisation of the study, contributed to the visualization of figures and tables, and supervised the research process. He played a key role in refining and editing the manuscript for scientific clarity and coherence.

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